

Contrastive analysis of rice grain classification techniques: multi-class support vector machine vs artificial neural network

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ABSTRACT

Rice is a staple food for 80% of the population in Southeast Asia. Thus, the quality control and classification of rice grain are crucial for more productive and sustainable production. This paper examines the contrastive analysis of rice grain classification performance between multi-class support vector machine (SVM) and artificial neural network (ANN). The analysis has been tested on three types of rice grain images which are Ponni, Basmati, and Brown rice. A digital image transformation analysis based on shape and color features was developed to classify the three types of rice grain. The performance of the proposed study is evaluated to 90 testing images of each rice variation. The ANN is observed to return higher classification accuracy at 93.34% using Level Sweep image transformation technique. Based on the results, it signifies that the ANN performs better classification than the multi-class SVM.

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1. INTRODUCTION

Rice grading is critical to determine the value of rice and its subsequent price on the market. It is an important process used in the rice manufacturing industry to ensure that the rice produced for the market meets the consumer's quality requirements. The grading methodology and determinants to be used for grading which usually referred to as rice attributes, are the two important aspects that need to be considered in deciding rice grades. Multi-class support vector machine (SVM) is a well-known method in the machine learning community for binary classification problems. On the other hand, a metaheuristic technique of artificial neural network (ANN) is preferred due to its universal approximation ability in image cataloguing and pattern recognition. In this research, the contrastive analysis between these two techniques of multi-class SVM and ANN for rice grain classification is presented.

This paper is divided into five sections. The first section consists of the introduction and research motivation. Second section comprises of the related literature review to rice grading endeavours. The third section is on methodology adapted in this research. Furthermore, section four entails the analysis and

findings of this research. Eventually, the last section summarizes the research findings respected to research objection, as well as recommendations for future research.

2. RELATED LITERATURES

Rice is a staple food for populations in East and South Asia, Latin America, India and Iran in particular [1]. Besides, it is a staple food for 80% of the population in Southeast Asia merely. As countries achieving self-reliance in rice production, customers have increased demand for better quality rice. The various rice types are a label of its marketable value, genetic and agronomic characteristics, and consumption quality. The rice quality is classified upon many parameters such as shape, size, color, and number of cracked kernels [2]. Such variables largely determine the grade and price of rice grain, but it remains difficult to achieve the objective and rapid measurement without the aid of precision techniques and instruments.

The quality control and classification of rice grain are crucial for more productive and sustainable production. Presently, the rice grain type and quality are rapidly assessed by the eye-naked inspection. However, this process of evaluation is complex, tiresome and time-consuming [3]. The decision-making capabilities of a rice grain inspector can be severely affected by the mental state induced by biases and work pressure, a physical condition such as fatigue, and working conditions such as inadequate lighting, and weather [4]. Additionally, the inspection is claimed to be very difficult and complicated [5]. During the handling of rice grain, information on the type and quality of rice grain is needed at several stages before the next operation can be decided and carried out. Even though the highly trained inspector can perform the quality inspection on few familiar types rapidly, this method is susceptible to exhaustion, highly subjective, and is impaired by environmental conditions and psychological weaknesses which lead to erroneous judgment [6].

Regardless of the weaknesses of the manual and visual methods, these methods remain the preferred techniques employed by the rice industry. It is due to the practicality and cost-effective as required in a competitive rice industry [7]. Hence, in view of this, an effective automated imaging system for rice grain classification is highly desirable. Machine vision and image processing are extensively used in biological and agricultural research [2]. It is a rapid, economical, coherent and realistic method of examination and assessment [8]. It enhances the computer technology by significantly reducing the cost of digital imaging hardware and software [9], and the reduction of time [10] exceptionally.

Up till now, a few numbers of researches have been conducted in estimating rice appearance quality inspection [11-25]. This paper, however, proposed a contrastive analysis of rice grain classification techniques between the multi-class SVM and the ANN. Feature extraction techniques of shape and color were implemented to analyse the characteristics of the rice grain. Whereas, a multi-class SVM and ANN techniques are used to classify the three types of rice grains which are Ponni, Basmati, and Brown rice. The classification performances of both techniques are then compared.

3. RESEARCH METHOD

The aim of this study is to compare the rice grain classification performance between two techniques of multi-class SVM and ANN. Figure 1 portrays the flowchart of this research. The details upon the data background can be referred in [1].

3.1. Rice grain images

Ninety testing images of three types of rice grains which are Ponni, Basmati, and Brown rice were collected. Table 1 presents the sample images for each type of rice grain as mentioned as in [11]. The dataset can be retrieved from rice grading database (RiGraDa) mobile application which can be downloaded from the link: <https://play.google.com/store/apps/details?id=com.mobileappvalley.android5da2810ca534c>.

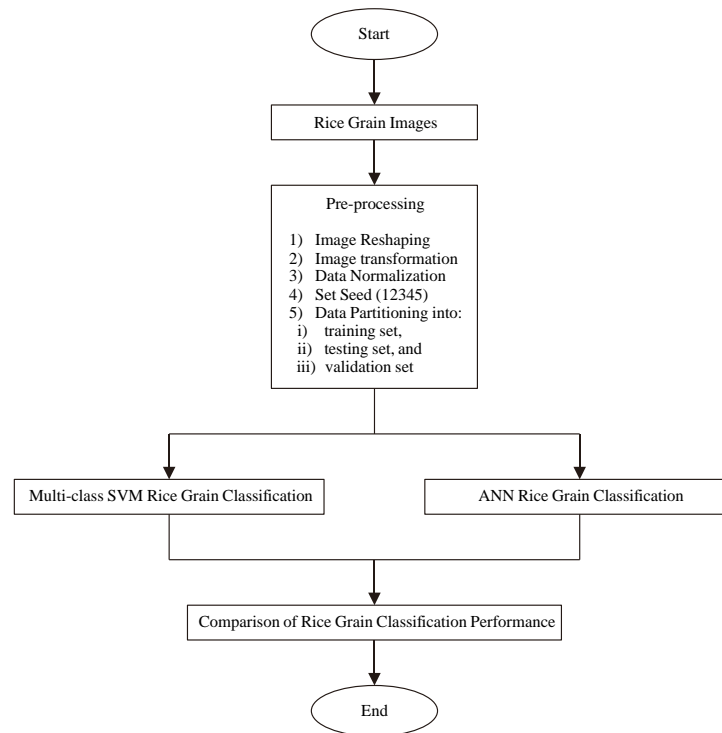


Figure 1. Proposed flowchart of rice grain classification

Table 1. Sample images of rice grain

Image	Type
	Basmati Rice
	Ponni Rice
	Brown Rice

3.2. Pre-processing

The pre-processing involves some processes in preparing the images for further analysis. In this study, the pre-processing includes a few processes which are image reshaping, image transformation, data normalization, and data partitioning. The implementation is performed using *R* software. After the dataset or rice grain images have been captured and collected, the images were then reshaped and transformed. In this research, three different techniques of pre-processing were adapted which are as follow:

1. Level Sweep [26] - Sweep: 1, Width: 110, Opacity: 1.
2. Gradient Magnitude [27] - Max: 94.73, Min: 0, Mean: 3.41.
3. Hysteresis Threshold [28] - Max: 255, Min: 0, Mean: 3.97, Std. Dev.: 31.58.

Figure 2(a-c) show the original images taken in laboratory. In the meanwhile, Figure 2(d-f) illustrate the sample outcome of the image reshaping and transformation for Level Sweep, Gradient Magnitude, and Hysteresis Threshold.

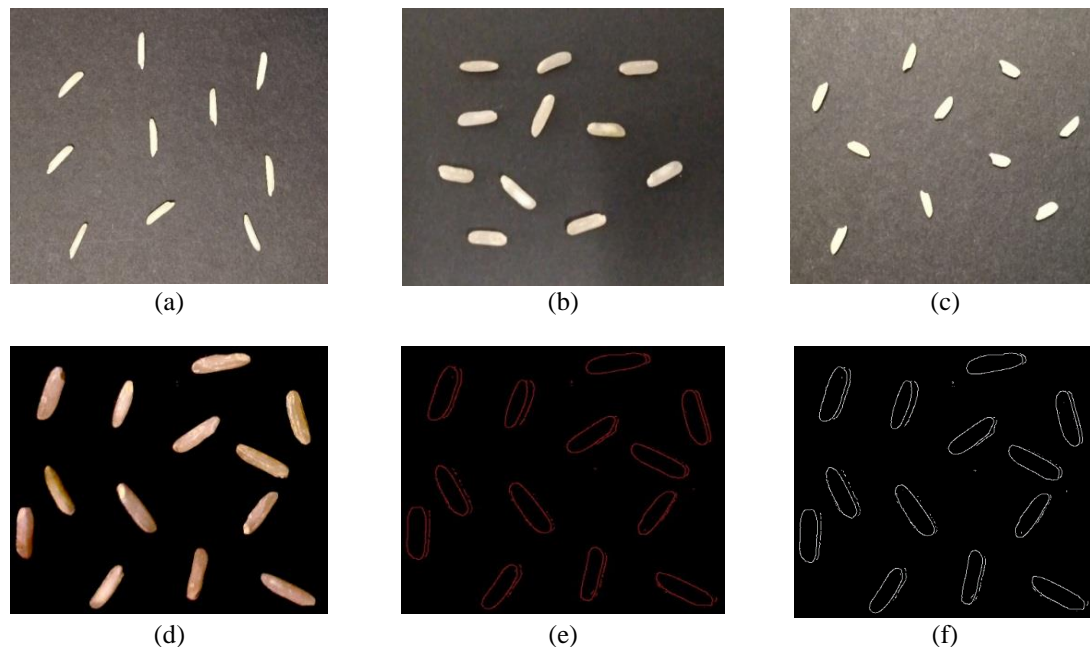


Figure 2. Original images taken in laboratory: (a) Basmati (b) Brown Rice (c) Ponni. Sample outcomes of image reshaping and transformation: (d) Level Sweep, Sweep: 1, Width: 110, Opacity: 1. (e) Gradient Magnitude, Max: 94.73, Min: 0, Mean: 3.41. (f) Hysteresis Threshold, Max: 255, Min: 0, Mean: 3.97, Std. Dev.: 31.58

Next, the images were then normalized from -1 to 1 scaling. In this research, two types of data partitioning were reformed which are:

1. 80% (training set), 10% (validation set), 10% (testing set) as in [29]
2. 70% (training set), 15% (validation set), 15% (testing set) as in [30]

3.3. Multi-class SVM rice grain classification

Subsequently, the image classification process is implemented to determine the type of rice grain from the uploaded input image. A multi-class SVM is employed for the classification of the rice grain. The implementation of the multi-class SVM could be done either experimentally [31] or conceptually [32]. It performs the classification by mapping the input vectors into a higher-dimensional space and building a hyper-plane that separates the data in the higher-dimensional space in an optimal way. The multi-class SVM is chosen as it has a bigger number of classes that can be classified [33], as compared to the SVM which is limited to only two types of classes. In this process, the training set was used to train the multi-class SVM model and the testing set was used to test the classification accuracy performance. The testing set is represented in (1) as follows:

$$X = \{(x_i, y_i)\}_{i=1}^l \text{ where } x_i \in R^n \text{ and } y_i \in \{1, 2, 3, \dots, c\} \quad (1)$$

There are various approaches of multi-class classification problem as discussed in [34-37] such as directed acyclic graph (DAG), binary tree of SVM, one-against-all (OAA) and one-against-one (OAO). In this study, the OAO technique for multi-class classification is chosen.

3.4. ANN rice grain classification

ANN is one of several machine learning algorithms that can help to solve classification problems. In this study, the ‘rule of thumb’ is adapted for the determination of hidden neurons in the hidden layer. Two-layer neural network with *tansig* and *tansig* transfer function [38-39] were implemented. The networks are used to evaluate the performance of the neural network. Figure 3 depicts the process flow of the ANN implementation.

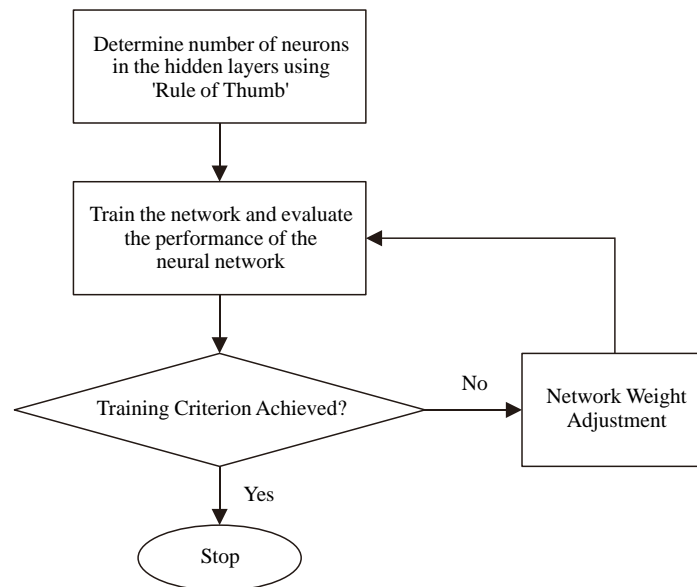


Figure 3. Process flow of proper neural network process

4. RESULTS AND DISCUSSIONS

The performance of rice grain classification for both multi-class SVM and ANN is measured using overall correct classification rate (OCCR). The OCCR results for multi-class SVM [11] and ANN is demonstrated in Table 2 and Table 3 respectively.

Table 2. OCCR of ANN

ANN Two layered: Sigmoid Purelin Configurations: 130-86-3	Level Sweep	Gradient Magnitude	Hysteresis Threshold
Data Partitioning: Train-Valid-Test 80-10-10	92.25%	89.92%	92.73%
Data Partitioning: Train-Valid-Test 70-15-15	93.34%	92.98%	92.62%

Table 3. OCCR of multi-class SVM [11]

Rice Grain	% of Accuracy
Basmathi	90
Ponni	93.33
Brown	93.33
OCCR %	92.22

Based on the OCCR results produced in Table 2 and Table 3, both ANN and multi-class SVM were observed to produce high classification accuracy. The OOCR recorded more than 90% for all categories except for Gradient Magnitude (Train-Valid-Test: 80-10-10) which only returned 89.92% of accuracy. The Level Sweep is monitored to return the highest value of OCCR which was 93.34% for Train-Valid-Test: 70-15-15 configurations. These reflect that the Level Sweep is the best pre-processing technique for this dataset of rice grain classification technique as compared to Gradient Magnitude and Hysteresis Threshold. Yet, the performance of Hysteresis Threshold could not also be underestimated as it returned 92.73% and 92.62% of OCCR values. The multi-class SVM, on the other hand, is observed to produce a competitive OCCR value at 92.22%.

The results showed high capability and potential of multi-class SVM [11] and ANN techniques in rice grain classification of Basmati, Ponni and Brown rice. The morphological features of shape and color are sufficient to be used as input variables to both multi-class SVM and ANN techniques in classifying the rice grain types with high accuracies. Based on the OCCR produces, the ANN is observed to return higher classification accuracy at 93.34%. Based on the results, it signifies that the ANN performs better classification than the multi-class SVM.

5. CONCLUSION

As a conclusion, the objective has been magnificently achieved. The application of multi-class SVM and ANN for rice grain classification to a variety of testing images has also been successful. Thus, with the comparatively high classification accuracies obtained, a machine vision framework and the established ANN architecture could be used as a tool to achieve more effective, precise and unbiased assessment of the rice classification at rice marketing points in the future. Yet, the results could further be improved by applying *tansig* and *tansig* transfer functions in both first and second layer, or possibly to increase the number of samples using rotation technique.

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